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Preference Extraction from EEG: An Approach to Aesthetic Product Development

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Abstract

This paper introduces a bio-signal based user-preference extraction methodology. The extensive literature review revealed that a large body of the relevant research focuses on the emotion recognition problem. While the potential impact to the industry is significant, the user preference detection by using EEG signals has not been addressed adequately in the literature. The results of a comprehensive experimental study suggest that the user preferences concerning the product design alternatives and offered functionalities of these products can successfully be extracted from brain signals using a single-electrode data collection scheme. Experiments were conducted on 14 subjects using pair of images where each image represents a product design solution. It was evident from the experiments that, strength of alpha-peak values captured from subjects are strongly correlated with the user preferences. While for the right-sided subjects, lower alpha-peak values correspond to the higher preferences, we observed an opposite relationship between the alpha-peak values and the preferences for the left-sided subjects. When the results of body response was compared with the user's opinion on preference, up to 90% of accuracy was observed.

Keywords
Preference extraction, Electroencephalography (EEG), Emotional valence

1. Introduction
It is crucial for product manufacturers to capture customer preferences accurately. Survey techniques, observations and usability tests are common practices that are utilized by organization in order to identify user preferences. While user expectations from a product can be retrieved through multi-criteria decision analysis such as Analytical Hierarchy Process (AHP), Fuzzy-based methods, or Scoring Matrix, how a user perceives the aesthetics and the functionalities of a design can only be measured through experiments with the actual or virtual design alternatives (Akgunduz, 2002). In this paper, we explored the pairwise alternative-comparison methodology in order to measure the preferences. Multi-criteria decision making methods enable us to rank alternative design solutions according user preferences that are obtained from pair-wise alternative comparisons experiments. In general a subject is asked to compare two competing design alternatives based on a pre-defined criterion. The quality of the procedure is strongly depending on the format of the question and the subjects' competence in correctly expressing his/her true feelings. Literature suggests that survey results may include situational bias of the participant (Buchanan, 1992). Our experimental study also concluded that the confusion of the participant regarding his/her true preferences play a role in the response.

In this research, we investigated the possibility of measuring the level of preferences from bio-signals. From the emotion detection literature, we know that human body reacts to the environment by producing various muscle contractions and bio-signals. The purpose of the study is to achieve unbiased user preference detection from body response so that the drawbacks of the survey techniques can be eliminated. The uniqueness of our approach is: i) bio-signals are retrieved from a single electrode from only a unique part of the brain; ii) reference based comparisons (results are evaluated for each individual independently). The proposed preference assessment methodology has been tested on several subjects. The results strongly support that, the user preferences can be captured from human emotion, in our case from brain signals. In order to achieve our objectives, we adapted a three-step approach.

First, body responses (in our case bio-signals) have been tested on image library that includes controversial images. The International Affective Picture System (IAPS) library that was developed by the NIMH Center for the Study of Emotion and Attention at University of Florida was used in our experiments. The IAPS database includes various powerful images that can generate strong body-responses. We tested our hardware and software on the IAPS library with an objective to measure the body responses as a means of bio-signals when a subject is exposed to controversial images. The test results clearly concluded that emotional valence actually relates to the preference of people (higher/lower values are normally indicating to the more/less-preferred images).

In the second phase, a data acquisition system and a data-analysis methodology have been established in order to extract emotional valence and user preference from EEG signals. In their work, Ansari-Asl, K., et al. (2007) successfully extracted numeric values of emotion dimensions from physiological responses such as Electrocardiogram (EKG) and skin conductance. Their work also concludes that a global numerical value cannot be established through physiological signals (for images in IAPS library) due to unique characteristics of each participant. Hence, in our work we focused on establishing a trend between the bio-signal values extracted for images and the order of preferences. Consequently, pairs of images that reflect extreme two cases (one is being pleasant, the other is being extremely unpleasant) were selected from the IAPS database. Participants were exposed to these images while their EEG data is stored in a database. Finally, a number of statistical analyses were conducted on the collected EEG data to verify if there exists a relationship between the EEG signal fluctuations and the participants' preferences. The results clearly demonstrated that the EEG signals have strong correlations with the preferences.

Finally, the developed preference extraction methodology has been tested on possible product design solutions in order to establish the link between the preference and the bio-signals. Tests, conducted on 14 subjects show that preferences can be extracted from bio-signals using a single electrode data acquisition system. The proposed bio-signal based preference extraction methodology has potentials to be integrated into product design and development processes in the near future.

2. Literature Review

While there is a healthy number of studies reported in literature concerning on the emotion recognition from EEG signals, the user preference detection from EEG signals has not been addressed adequately in the literature. In this section, we reviewed the emotion recognition literature in details (Ansari, 2007, Bradley, 2007, Coan, 2004, Cuthbert, 2000, Davidson, 1992, Han, 2006, Lang, 2008, and Horlings, 2008). Furthermore, the relevant literature on the preference identification, preference development in person's mind and cognitive and affective preference topics has been discussed.

2.1 Aesthetics and Preference Extraction

Aesthetic design has become an important issue in product design and development. In today's highly competitive marketplace, manufacturers are pressured to design products that not only satisfy customers with their usability and included features, but also capture customers' attentions with their aesthetics and styles. Lingaard (2007) reported on the relationship among aesthetics, product usability and user satisfaction. He reported that customer satisfaction can be increased with products that offer more aesthetic appeal than usability characteristics. To understand why people are satisfied with products that provide more aesthetic appeal than its functionalities, Psychologists have studied the process of visual preference development in human mind. Leder et al (2004) concluded that the preference for an art work builds in human mind in five different stages. Two possible outcome of this process is observed: aesthetic emotion, and aesthetic judgment. In our case, the preference identification from product images, visual presence of images and cognitive judgment of user are the two important inputs. The visual appeal of the image includes the visual presence of the product and perceptual variables of the image. The cognitive judgment of the user considers all previous experiences or information concerning the product. The output, in our case is the preference of a participant, consists of two components: affective preference based only on the aesthetic appearance; and cognitive preference built on previous experiences and expectations.

The work of Lingaard (2007) enabled us to determine whether we were receiving the affective preference or the cognitive preference of participants. Lingaard (2007) reported that if a visual stimulus stays for only 50 milliseconds, the response is purely intuitive, i.e., it does not consider cognitive thinking. This response takes place

in the amygdala which is located in the posterior part of the brain and unreachable with external EEG electrodes. Our experimental results concluded that, when participants were stimulated for more than 5 seconds, the retrieved body response represents the cognitive preference of participants.

Another line of research closely related to our work is the preference extraction from brain activities. In their works, Vartanian and Goel (2004) used fMRI imaging in order to capture the human preferences. They successfully identified that participants disliked the images of altered (blurred) artwork when they were compared with the originals. Reports on extraction of preference from brain imaging like fMRI are also found in literature on neuromarketing. Sutherland (2007) reported that fMRI images were used by Daimler Chrysler in order to capture the customer preferences. fMRI images concluded that images of sport cars trigger the "rewards region" of the brain. Similar results were obtained in studies related to the alcohol, drug and sex. However, accessing to a fMRI system in order to capture the data from sufficiently high number of subject is almost impossible.

2.2 Dimensional Models of Emotion

There are different models to describe emotion. In our research, we focused on dimensional models as they are easy to analyze and pertinent to previous emotion recognition studies. Russel (1980) proposed the two-dimensional circumflex-model that governs 28 different emotions in the valence-arousal space. Bradley and Lang (1994) suggested a three-dimensional model where valence, arousal and dominance are the dimensions of emotion. In this model, valence addresses the quality of emotion ranging from unpleasantness to pleasantness; arousal refers to the activation level of an emotion ranging from calm to excitement; and dominance relates to the feeling of control over a situation that ranges from weak to strong. The arousal and valence are the most frequently used dimensions in the literature. We analyzed the emotional dimension ratings of IAPS images and found that the emotional dimension valence is directly related to preference of images. Figure 1 (a) shows the simplified two dimensional model of emotion proposed by Russel (1980).

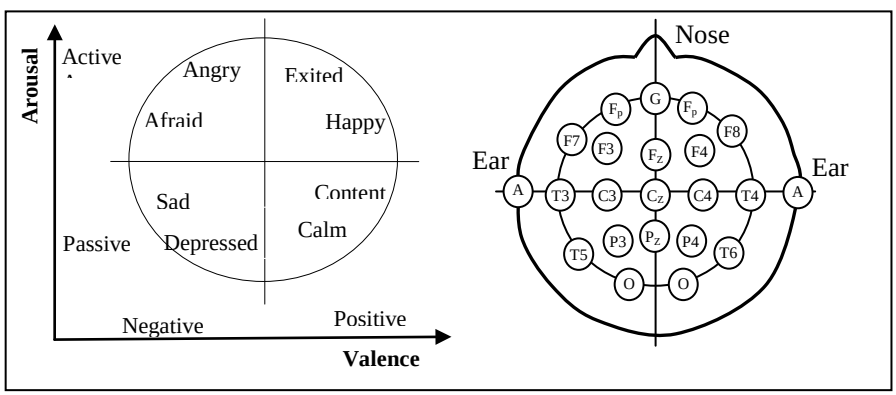

Figure 1: (a) Two dimensional model of emotion (left), (b) The 10-20 Electrode Positioning System (right)

2.3 EEG and Emotional Valence

Davidson (1992) reported that left and right hemispheres of the brain are specialized for identifying different classes of emotions. Left anterior hemisphere is specialized on approach and right anterior hemisphere is responsible for withdrawal. Bos (2007) reported that the low activation of left and right hemispherical (inactivation of brain) is a measure for valence. Left frontal inactivation is an indicator for the withdrawal response or negative emotion, and right frontal inactivation is a sign of an approach response or positive emotion. It was also reported that high alpha activity (8-12 Hz) is an indication of inactivation (Mandryk and Atkins, 2007). The work by Kostiyunia and Kulikov (1996) showed that different emotional states generate different peak frequencies in the alpha band. In our preference extraction study, we used alpha-peak frequencies received from virtual data channel. Some researchers suggested that the best positions to place electrodes on skull in order to collect the alpha peak frequency are F3 and F4 position in Figure 1 (b) (Horling, 2008). The quality of signals we acquired in our study further supported the literature. Our initial experiments with 3 subjects concluded that higher values of alpha-peak-frequency average meant less preference when EEG was taken from F3 in Figure 1 (b); and higher values of alpha-peak-frequency average meant higher preferences when EEG was taken from F4 in Figure 1(b).

Sciffer et al. (2007) reported that there is no empirical support for hemispherical emotional valence theory that claims left and right side of the brain are dominant for negative or positive emotions. They reported that for different people, the response to positive or negative emotion and activity on a particular side of brain varies. While we conducted our study with IAPS image library with three participants (phase 1), we found only one type of response that higher values are associated with lower preferences when data is captured from location F3 in Figure 1(b). Still we kept provisions to check the left/ right sidedness of the brain in our experiments with the product design images (phase 2). Our phase 2 experiments showed that some of the subjects generate opposite results than expected: that higher values are associated with higher preferences when data is captured from F3. We were able to explain the conflicting results with these subjects being the right-sided. An opposite hypothesis was applied in order to evaluate right-sided subjects. Assigning people to be left/right sided started with naming the first participant to be left sided and people showing opposite results to be right sided.

3.0 System Design

The objective of the work presented in this paper is to validate if customer preferences can be captured from the bio-signals. In order to achieve these objectives, EEG signals were collected from subjects while they interact with images (AIPS library or product features) and a number of statistical analysis have been applied to derive meaningful results. In sum, we focused on investigating the following two hypotheses:

Hypotheses 1:
H_0: User preferences can be captured from EEG signals when the signals are acquired from a single channel source
H_1: User preferences cannot be captured from EEG signals

Hypotheses 2:
H_0: EEG values are correlated with preferences but the level of correlation varies with electrode positioning and sidedness of the participant
H_1: EEG values are not correlated with preferences and/or electrode positioning and sidedness of the patients is not a factor

Below, the characteristics of hardware and software used in the experiments are discussed and the details of data collection and analysis protocols are provided.

3.1 System Components and Software

Computer: All experiments have been conducted on an Acer Aspire 4736Z laptop with dual core Intel Pentium T4200 processor and 3 GB DDR3 memory, 320 GB hard disk space where two monitors, 14-inch and 17-inch were used as a display.

Signal Processing Hardware: ProComp2 system from Thought Technology (TT) that includes a signal encoder to digitize signals, a USB receiver kit to transmit digitized signal to computer, a fiber optic cable to connect signal encoder and USB receiver kit, a USB cable to connect USB receiver kit with computer, an EEG electrode to place on skull and an ear clips to attach to an ear was used.

Signal Processing Software: For data-collection and data processing, BioGraph Infinity and EEG Suite from Thought Technology were utilized. For visual display of data in real-time Screen Editor from Thought Technology was used. Results were analyzed in Microsoft Excel and Minitab software.

3.2 Data Collection Protocol

A data collection protocol has been developed according to the safety rules that are recommended by the equipment manufacturer and previous works related to EEG data collection. Prior to the experiments, the purpose of the study was clearly explained to participants and their written consents were obtained. Once the consents were obtained, 12 subjects were invited individually to participate in the study. In order to capture the EEG signals, a single electrode was attached to the subject's forehead. While images were displayed on the 17 inches monitor, EEG signals were recorded for statistical analysis. In order to verify the accuracy of the described preference detection from EEG signals, subjects were asked to provide their preferences verbally. In order to obtain the objective measure of subject preferences, a pair-wise comparison technique has been implemented.

3.3 Data Collection, Processing and Export

The infinity software is used to visualize and record the raw EEG signals. Subject's ID, location of electrode, experiment number, and raw EEG signal with respect to time were recorded for each subject. Using the Biofeedback software, the noise and artifacts in the raw EEG signals were filtered out. Once the data collection is completed, the saved data was exported as text file for further statistical analysis

3.4 Data Analysis Process

In order to test if the hypothesis, which is "EEG signals reveals the preferences", is correct, following statistical analysis were performed using Excel Analysis Engine. First, stimuli associated average or Root Mean Square (RMS) of time-series data was obtained. Next, the linear-trend line analysis was performed to find trends of data associated with the two types of images (high preference vs. low preference). The mean differences of the alpha-peak values obtained for each subject for each experiment was tested using student t-test in order to determine the statistical significances. After finding statistical significance, the hypothesis relating to EEG signals and preferences was confirmed and used for the rest of the study. After capturing phase 2 data, paired t-tests were done to find significance of phase 2 findings with real product images as well.

4. Phase 1 Experiments

In order to conduct the phase-1 experiments, three image-pairs were selected from the IAPS image library (see table 1). The emotional valences of images in each image-pair were strongly correlated in negative direction.

We considered the IAPS image with the higher valence rating as high-preference image and the one with lower valence rating as low-preference image. Placement of high/low preference image was altered among tests.

Table 1: IAPS Image Sets for Phase-1 Experiments

Image Set	Image No.	IAPS No.	IAPS Name	Image subject/ Description	Valence Mean (SD)	Arousal Mean (SD)
Food	1	7330	Ice cream	An Ice cream scoop	7.69(1.84)	5.14(2.58)
	2	7360	Pie & Bug	A pie with flies on it	3.59(1.95)	5.11(2.25)
Nature	1	9341	Pollution	A polluted river	3.38(1.89)	4.50(2.10)
	2	5829	Sunset	Sunset in a beach	7.38(1.31)	4.52(2.48)
Baby	1	2095	Toddler	A poor and sad baby	2.16(1.31)	4.69(2.11)
	2	2071	baby	A smiling baby	7.45(1.24)	4.60(2.03)

4.1 Experiment 1: Establishing relations between values and preferences

The objective of the Experiment 1 is to validate if $V^i < V^j$ then image i is more preferred than image j by the subject where V^i is the mean valence, measured for image i from the left frontal part of the brain.

We used 3 stimuli slideshows with 5 second preparation time and 5 second image display time. Data was collected from a participant for all three image-sets for 15 sessions. The average alpha peak frequencies for high-preference and low-preference images from the three stimuli sets were measured. In order to establish the correlation between EEG and preferences, plot diagrams of data and trend lines were obtained to observe the clustering tendency of values. Moreover, a paired-T means test with data from all three image sets was performed to find the tendency of mean differences in recorded data. The trend lines for image set 'Food' is given in figure 2. Trend lines for other two experiments show similar characteristics.

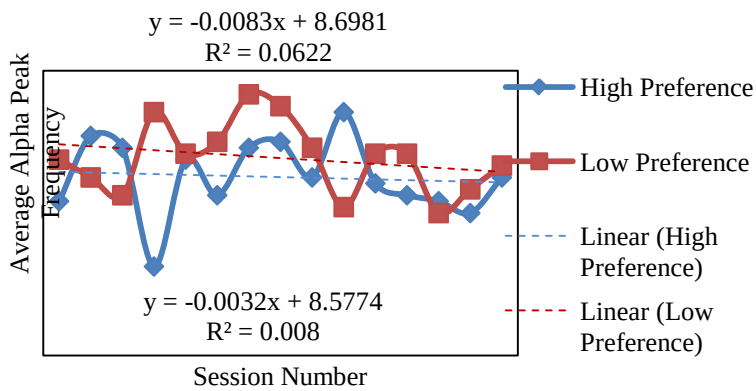

Figure 2: Alpha-Peak values and Linear Trend lines for Experiment with 'Food'

The data from test 1 (all three image sets) were used for a paired t-test with 95% confidence level. The difference between the data associated with high preference image sets and low preference image sets are used as input data for the t-test. Results show that the difference between high preference image values and low preference image values is statistically significant. Experimental results show that alpha peak frequency averages are inversely related to the preference of images when EEG is captured from the left frontal side of the brain.

4.2 Experiment 2: Identifying Different Electrode Positions

While experiment 1 demonstrates that preference can be captured from the EEG signals, the results itself do not ensure if the left frontal side of the brain is the best location to collect EEG signals. Hence, further experiments were conducted to test the quality of signals received from other available locations of skull. Since large part of the skull is covered by hair, only two other locations (see figure 1 b): right side of the brain F_3 to test monopole measurements; and between F_3 and F_4 of forehead to capture dipole measurements. In this experiment, we also tested the feasibility of capturing preferences from a single session of data as opposite to 15 sessions of experiments conducted for the Experiment 1.

Three subjects were invited to participate in the experiments that included three pairs of IAPS images. For each image set, a single set of data was captured from three different parts of the skull (monopole from F_3, dipole from between F_3 and F_4, and monopole from F_4 (as in figure 2 b). The results are summarized in Table 2. From Experiment 2 we find that the best results are obtained for monopole data collection from F3 position. Moreover, the results show that it is possible to achieve up to 78% of accuracy in identifying preferences from only a single session of data. We also came up with the first working hypothesis H_2 that addresses electrode positioning and participant's sidedness.

Table 2: Results for phase-1 Experiment 2

Electrode Position	No of Partici-pant	No of Image Sets	total relations	No of Accurate relations	Accuracy/ trend
F3 Monopole	3	3	9	7	78%
F4 Monopole	3	3	9	5	56%
F3-F4 Bipole	3	3	9	67% positively related	

5. Phase-2 Experiments

In the second part of the experiments, the real product images were used to extract the user preferences. Eleven volunteers participated in 12 different experiments. A two-step approach has been followed. First, IAPS images were used to determine the sidedness of participant. While for the right-sided subjects, lower alpha-peak values correspond to the higher preferences, we observed an opposite relationship between the alpha-peak values and the

preferences for the left-sided subjects. In the second level of experiments, various product images were used to extract user preferences. For example, if a participant accurately identified his/her preferences according to preliminary hypothesis (at least three out of four level-1 experiments), we considered the participant to have left sidedness and continued to use the same hypothesis for the level-2 experiments. If a participant failed to identify preferences from the level-1 experiments, we considered that he/she has right sidedness, and used reverse/opposite hypothesis to analyze level-2 experiments.

5.1 Image Selection for Experiments

In level-2 experiments with product images, we used two competing product images for each experiment (See figure 4). Image sets used for the phase-1 experiments are given in Figure 3. Each image was displayed for 7.5 seconds and a preparation time for 7.5 seconds was given between each image. Description of the images used in this phase is discussed below.

Table 3: IAPS Image for Phase 2 level-1 Experiments

Exp No & Image Set	Image No.	IAPS No.	IAPS Name	Image subject/ Description	Valence Mean (SD)	Arousal Mean (SD)
1. Food	1	7330	Ice cream	Ice cream scoop	7.69(1.84)	5.14(2.58)
	2	7360	Pie & Bug	A pie with flies	3.59(1.95)	5.11(2.25)
2. Sea Mammal	1	1931	Shark	A scary shark	4.00 (2.28)	6.80 (2.02)
	2	1920	porpoise	Two dolphins	7.90 (1.48)	4.27 (2.53)
3. Nature	1	9295	Garbage	A garbage dump	2.39 (1.30)	5.11 (2.05)
	2	5199	Garden	A flower garden	6.12 (1.72)	4.44 (2.20)
4. Dogs	1	1302	Dog	A scary dog	4.11 (1.88)	6.08 (1.95)
	2	1710	Puppies	3 funny puppies	8.59 (0.99)	5.31 (2.54)

Table 4: Image Thumbnails of Phase-2 Level-2 Experiments

Exp. No	Experiment Name	Image 1	(Name and Source)	Image 2	(Name and Source)
5	Manual transmission		1. Leather stick[1]		2.Metal stick[3]
6	Automatic transmission		1. Grooved slot[1]		2. Simple slot[2]
7	Sedan colors		1. Black sedan[2]		2. White sedan[2]
8	Hatchback colors		1. White hatchback[2]		2. Dark golden hatchback[2]
9	Auto/Manual transmission		1. Sedan + manual[1]		2. Sedan + auto[2]
10	Car background		1. Background[2]		2. No background[2]
11	Car model		1. Sedan[2]		2. Hatchback[2]
12	Gas pedal		1. Studded[2]		2. Striped[4]

[*Image Source:* [1]www.toyota.com, [2]www.honda.com, [3]www.redflagdeals.com, [4]www.cadillucforums.com]

5.2 Analysis of Results

Two participants showed 50% accuracy in level-1 experiments, so we could not identify their sidedness. They showed similar results in level-2 experiments as well so we removed their data from further analysis. The results are summarized in Table 5. In some cases, our results revealed confusion in affective and cognitive preference. For example, a participant is identified as he prefers the image of a manual transmission, however in his interview; he stated that he prefers driving an automatic transmission (experiment 9). The detailed interview with the subject revealed that his answers were not the actual preference rather they were his logical reasoning as in this particular case, a manual transmission is a common choice and more family members can handle it. Hence, we did not consider them as wrong answers and treated separately. For some experiments, participants could not identify their preference by viewing images. We marked those results as undefined and did not include in calculations.

5.3 Statistical Analysis of Results

For level-1 experiments, we considered all data related to IAPS images for 9 participants (as we removed data of two) and used for paired t-test with 95% confidence level. For level-2 experiments, we considered data related to product images for 9 participants and used for paired t-test with 95% confidence level. We separated data according to preference mentioned by participants and included wrong answers. For 7 instances, participant's cognitive preference and affective preference conflicted. We placed those data according to their cognitive preference. We also combined data of left sided and right sided people by placing higher values together. The summary of the results is given in Table 5.

Table 5: Accuracy analysis for Phase-2 experiments

Participant Accuracy			
ID	% Accuracy Level 1	% Accuracy Level 2	% Accuracy Overall
101	75	100	89
102	75	100	90
103	50	72	64
104	75	86	82
105	75	80	78
106	75	60	67
107	100	57	73
109	75	29	45
110	75	86	82

Test Accuracy		
Level	Test Name	% Accuracy
Level 1	Test 1 Food	67%
	Test 2 Sea Mammal	78%
	Test 3 Nature	56%
	Test 4 Dogs	100%
Level 2	Test 5 Manual	43%
	Test 6 Auto	63%
	Test 7 Sedan color	85%
	Test 8 Hatch. Color	75%
	Test 9 Auto/ Manual	100%
	Test 10 Background	100%
	Test 11 Model	67%
	Test 12 Gas pedal	67%

6. Conclusion

The objective of the study was to capture the product preferences from brain signal. In order to validate our claim, we built an experimental set up to capture participants' bio signals from a single electrode and conducted two rounds of experiments. First, we measured the relationship between preferences and the strength of signal (alpha peak frequency) captured from user on images selected from IAPS database. In the second phase, we tested our approach on 11 different users on 12 different experiments in order to capture their preferences on product design. Experimental results show that the user preferences can be captured from bio-signals through a pair wise comparison scheme. While there is a strong relationship between alpha peak frequency values and preference when it is captured from the same user, inter-user comparison is not possible. For instance, while the captured alpha peak frequency value for one of the users indicates the low preferences, same value might correspond to high preference for another user or another test. As a result, we analyze the average alpha peak frequency values for each subject independently and consolidate the results for all the users to determine the existence of a trend. Furthermore, the study identified cognitive preference of participants when both the cognitive and affective preferences present. To capture the affective preferences only (which reflect aesthetic beauty), factors affecting cognitive preferences were

kept neutral for the competing images. We believe it can be used in identifying user/customer preferences at different stages of product development process. We also feel that there is a gap in the fields of Neuromarketing requiring easy methods to extract preferences from brain activity. The findings from this study can very well address this issue. The method for preference extraction can be extensively utilized in Neuromarketing and marketing research. On-line or off-line gaming can use this method as a tool to increase interactivity among gamer and games. For example, choice of weapon or action to take can be aided with a head mountable device. The method can become an essential tool for online shopping. There are ethical concerns on the issue, which requires attention though.

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